IN THE UNITED STATES BANKRUPTCY COURT
FOR THE DISTRICT OF DELAWARE

In re:	Chapter 11
FTX TRADING LTD., *et al.*,[1]	Case No. 22-11068 (JTD)
Debtors.	(Jointly Administered)

DECLARATION OF KEVIN LU IN SUPPORT OF MOTION OF DEBTORS TO ESTIMATE CLAIMS BASED ON DIGITAL ASSETS

I, Kevin Lu, hereby make this declaration (this "Declaration") under penalty of perjury pursuant to 28 U.S.C. § 1746 and state as follows:

1. I am a Director of Data Science & Product at Coin Metrics, Inc. ("Coin Metrics"), a firm that provides cryptocurrency-related network data, market data, indexes and network risk solutions to financial institutions and companies in the digital assets industry. I have extensive experience working with pricing data in the field of investment management with domain expertise in cryptocurrencies and digital assets. I am duly authorized to make this declaration (this "Declaration") on behalf of Coin Metrics, and submit this Declaration in support of the *Motion of Debtor to Estimate Claims Based On Digital Assets* (the "Motion").[2] Except as otherwise noted, I have personal knowledge of the matters set forth herein and, if called as a

[1] The last four digits of FTX Trading Ltd.'s tax identification number are 3288. Due to the large number of debtor entities in these Chapter 11 Cases, a complete list of the Debtors and the last four digits of their federal tax identification numbers is not provided herein. A complete list of such information may be obtained on the website of the Debtors' claims and noticing agent at https://cases.ra.kroll.com/FTX. The principal place of business of Debtor Emergent Fidelity Technologies Ltd is Unit 3B, Bryson's Commercial Complex, Friars Hill Road, St. John's, Antigua and Barbuda.

[2] Capitalized terms used but not otherwise defined herein shall have the meanings set forth in the Investment Services Agreement.

witness, I would testify thereto.

Qualifications

2. I studied at the University of California, Berkeley, where I received a Bachelor of Science in Business Administration and a Bachelor of Arts in Economics, with distinction.

3. My professional experience consists of 15 years at several companies, during which I have specialized in performing analyses using applications of data science to financial data. For the past five years, I have worked in the digital assets industry where I have had direct experience in calculating prices for cryptocurrencies. Below I describe my relevant professional experience in chronological order.

4. From 2007 to 2009, I served as a Research Associate, and later an Associate Analyst, at NERA Economic Consulting, a firm that provides consulting services and expert testimony to government agencies and corporations. In this role, I conducted econometric and statistical analyses in connection with securities litigation, including measuring the impact of financial fraud on stock prices.

5. From 2011 to 2013, I served as a Senior Consultant, and later a Managing Consultant, at Edgeworth Economics, a firm that provides economic analysis and expert testimony in connection with commercial litigation. In this role, I performed analysis using applications of data science, finance, and economics for corporations involved in mergers and acquisitions, price fixing, and intellectual property disputes.

6. From 2013 to 2015, I served as a Data Analyst at Bridgewater Associates, an investment management firm that serves institutional investors. I initially served as a member of the data team in Bridgewater Associate's research department, where I created and maintained economic and financial data sets that are used in the firm's systematic trading systems. My responsibilities later expanded to include producing Bridgewater's Daily Observations, the

firm's flagship subscription research paper sent to institutional investors and policymakers. I regularly interacted with datasets, developed internally and sourced from major financial data providers, involving financial price timeseries across multiple asset classes and across multiple geographies.

7. In 2018, I served as Director of Quantitative Analysis at Element Group, a financial services firm that specializes in digital assets. I worked in the firm's asset management division and was responsible for engineering the firm's data analysis systems and developing systematic trading strategies. In this role, I regularly interacted with a wide selection of pricing-related datasets from cryptocurrency exchanges and cryptocurrency data providers.

8. I currently hold the position of Director of Data Science & Product at Coin Metrics. I joined the firm in 2019 and have played a key role in the development of the Coin Metrics Prices (as defined below), including evolving it from inception into an established commercial offering. The "Coin Metrics Prices" are a collection of prices for cryptocurrencies that are used by companies in the digital assets industry. As part of the initial development of the Coin Metrics Prices, I extensively reviewed the financial pricing literature within both the digital assets industry and the traditional financial assets industry. I have reviewed most publicly-available pricing methodologies from government agencies and major financial data providers. I have reviewed guidance regarding pricing assets published by the Financial Accounting Standards Board (FASB), the International Accounting Standards Board (IASB), and the International Organization of Securities Commissions (IOSCO) and have incorporated their standards and principles in the development of the Coin Metrics Prices. I have conducted extensive backtesting of multiple pricing methodologies and have first-hand experience in

observing how pricing methodologies perform during times of market stress.

9. For the past five years, on a daily basis, I or others working at my direction have performed routine examinations on the performance of the Coin Metrics Prices. My responsibilities also include regularly investigating and responding to price challenges and questions raised by Coin Metrics' users, which include exchanges, custodians, and asset managers.

10. I additionally hold the position of Chairperson of the Coin Metrics Oversight Committee, where I am responsible for maintaining the integrity of, among other things, the Coin Metrics Prices.

Coin Metrics

I. The Assignment

11. Coin Metrics was asked by the Debtors to provide pricing for certain spot assets listed on the FTX exchanges ("FTX") to assist the Debtors in determining the value of claims on account of digital assets as of November 11, 2022 at 10AM ET (the "Petition Time"). As detailed below, Coin Metrics provided pricing for 428 spot assets, including spot tokens and stablecoins.

II. The Coin Metrics Prices

12. In determining the prices for the set of spot assets listed on the FTX exchanges, I heavily relied upon existing data products and methodologies developed by Coin Metrics. Therefore, in this section, I describe the qualifications of Coin Metrics with a focus on discussion of the Coin Metrics Prices.

13. Coin Metrics was founded in 2017 as one of the earliest providers of cryptocurrency network data. Since then, the firm has raised over $50 million in multiple rounds of financing. The firm's investors include both venture capital firms and strategic investors. The

firm's clients include some of the largest and most prominent institutions engaged in the digital assets industry.

14. I developed, and currently maintain, the Coin Metrics Prices, one of the commercial data products offered by Coin Metrics. Coin Metrics publishes a collection of prices for a set of cryptocurrencies consisting of the Coin Metrics Reference Rates and the Coin Metrics Principal Market Prices, which are collectively referred to as the Coin Metrics Prices. The Coin Metrics Reference Rates represent the price of an asset as calculated by a pricing methodology developed by Coin Metrics, and the Coin Metrics Principal Market Prices represent the price of an asset derived from the asset's principal market, the market with the most trading volume or activity. As discussed further below, I utilize the calculation methodologies contained within the Coin Metrics Prices in determining the prices for the FTX digital assets.

15. The Coin Metrics Prices have become widely used within the industry. Coin Metrics' clients use the Coin Metrics Prices for research, for accounting and financial reporting, to settle financial contracts, to create financial products, for display purposes, and to publish on-chain via blockchain oracles. The Coin Metrics Prices also serve as an input in the Coin Metrics Bletchley Indexes, a suite of cryptocurrency benchmarks, as well as other benchmarks that Coin Metrics creates for clients in connection with a financial product.

16. Over the past five years, I have regularly examined the performance of the Coin Metrics Prices and have found that they consistently perform well, even during times of market volatility and market stress. My review has included several instances in which the Coin Metrics Prices are resilient to outliers, flash crashes, and suspected market manipulation.

III. Coin Metrics Data Quality

17. In determining the prices for the set of spot assets listed on FTX, I heavily relied upon the trades dataset maintained by Coin Metrics, consisting of executed trades between

buyers and sellers sourced from major cryptocurrency exchanges. Since the quality of the prices produced in this matter are in part dependent on the quality and completeness of the underlying data, in this section, I describe Coin Metrics' data collection system with a focus on data quality.

18. Generally, there are no requirements for cryptocurrency exchanges to report their trading activity to a centralized database representing a canonical source of truth, such as the Consolidated Tape System for equities in the United States. Therefore, cryptocurrency data providers must maintain infrastructure to collect data directly from each individual exchange. This represents an engineering task of high complexity. Many exchanges additionally only allow real-time data collection for certain data types and do not allow data providers to obtain historical data. Consequently, if real-time data collection is interrupted in any manner, it can result in a persistent void within the data provider's dataset, compromising its overall data integrity. These circumstances mean that no cryptocurrency data provider can claim with absolute certainty that the datasets they maintain are entirely complete and accurate.

19. To deal with these circumstances, Coin Metrics has expended considerable effort in engineering a data collection system that is resilient, robust, and possesses high levels of availability, reliability, and redundancy. This allows Coin Metrics to maintain one of the most complete cryptocurrency trades datasets in existence.

20. As an illustration of Coin Metrics' data quality, in 2021, Bitwise Investment Advisors, LLC ("Bitwise") submitted an analysis to the Securities and Exchange Commission (the "SEC") that examined the lead-lag relationships between Bitcoin's spot and futures markets in response to questions raised by the SEC regarding Bitwise's application to list a Bitcoin exchange-traded fund. To conduct this analysis, Bitwise had to obtain a trades dataset of high quality. As a result, they meticulously evaluated 29 data providers and chose 14 of them based

on various criteria, such as data coverage and data quality. Bitwise requested identical samples of trades from the 14 data providers, and after performing thorough due diligence, elected to use Coin Metrics as the lead data provider for their analysis. In their filing, Bitwise stated:

> "Based on this analysis, we elected to use Coin Metrics as the lead data provider for our analysis. At the time, Coin Metrics offered coverage of 26 exchanges, and had exceptionally high data quality. We compared these trades with data from participating data providers, looking for three types of errors: duplicated trades, erroneous trades, and missing trades. Coin Metrics had zero data errors, while its competitors had between two and 4,929 errors."[3]

21. Coin Metrics utilizes a multifaceted approach to ensure high levels of data quality and data integrity. Coin Metrics collects data from exchanges with at least two different applications, each located in an independent data center. For certain data types, Coin Metrics collects data from an exchange's HTTP application programming interface ("API") and websocket API simultaneously as an added redundancy measure. The system utilizes multiple proxy servers to ensure that throttling limitations imposed by some exchanges to limit downloading of data, known as rate limits, do not impact data collection. Each server that hosts the data collection applications has local database storage as a backup measure in case of a failure in the primary database.

22. Coin Metrics utilizes two geographically-separated and vendor-independent data centers. Each data center contains an independent and complete collection of the infrastructure and applications needed to collect, process, and serve the data. In the case of failure of one of the data centers, the Coin Metrics systems will automatically use the secondary data center with no action needed to be taken by users.

23. A dedicated internal team of data quality and site reliability engineers monitor

[3] https://www.sec.gov/files/rules/sro/nysearca/2021/34-93445-ex3a.pdf

logs and telemetry from Coin Metrics' servers, databases, and applications in real-time using a suite of dashboards and automated alerts. Coin Metrics also has dedicated monitoring to detect interruptions of service from an exchange, incidents reported by an exchange, or breaking changes to their API. This monitoring allows Coin Metrics to take swift corrective or mitigating action if necessary.

24. The processes utilized by Coin Metrics are governed by a series of Service Organization Control ("SOC") controls. SOC is a framework developed by the American Institute of CPAs for technology organizations and is based on several criteria that companies must follow to demonstrate their commitment to certain security measures and controls. The controls at Coin Metrics cover a wide range of processes utilized at Coin Metrics, including process integrity, vendor management, infrastructure, quality control and incident management, software development operations, information technology operations, information technology security, policy management, risk management, and security training. This collection of controls is designed to ensure that the systems (and adjacent systems) used to collect, process, and store Coin Metrics' data are maintained with processes that adhere to high levels of security and integrity. Coin Metrics received our SOC 2 Type 1 certification from Deloitte in August 2021 in the service areas of security, availability, and processing integrity.

25. This data collection system has allowed Coin Metrics to collect all, or substantially all, executed trades on major cryptocurrency exchanges, including FTX. Coin Metrics believes it has collected all trades for all digital assets listed on FTX that were available through their public API.

Documents and Data Reviewed

26. As part of my assignment, I have reviewed materials from Alvarez & Marsal ("A&M"), the Debtor's financial advisor, containing the symbol and name of 428 digital assets

that were at one point listed on FTX, along with some supplemental information indicating the type of digital asset. I also reviewed materials from A&M representing an export from the Debtors' database containing the full name of each digital asset.

27. Additionally, I have reviewed Coin Metrics' trades, historical market data, and pricing datasets for a wide selection of exchanges, including FTX, and for a wide selection of assets, with particular focus on the time range preceding the Petition Time.

Methodology Discussion

28. In this section, I describe the main facets of the methodology I use to calculate prices for the 428 digital assets identified in the scope of my assignment. I have relied heavily on the existing methodology used to generate the Coin Metrics Prices, and the methodology I have used in this assignment is generally identical to the methodology used to generate the Coin Metrics Prices with minor adjustments necessary to price certain FTX digital assets.

29. Generally, a methodology to calculate prices for digital assets must address two fundamental issues. The first issue relates to how to identify and select high-quality constituent exchanges and markets to be used as inputs into the price calculation. There are several hundred cryptocurrency exchanges in existence and a given instrument can be listed for trading on multiple exchanges. There are varying levels of quality across exchanges, and it is widely recognized within the industry that some exchanges engage in wash trading or other deceptive means to inflate their reported trading activity. Therefore, a process for evaluating and selecting high-quality and trustworthy exchanges is a necessary component of a pricing methodology. Once a set of high-quality exchanges has been selected, one must then identify the specific markets (or "constituent markets") to select, since a digital asset may trade on multiple markets for a given exchange. A process for evaluating and selecting high-quality markets is also a

necessary component of a pricing methodology.

30. The second issue relates to the statistical techniques used to combine data from constituent exchanges and markets to calculate a price. Pricing methodologies generally use some measure of central tendency, such as averages or medians, to combine input data in the price calculation.

31. I divide the methodology into five steps to address these issues. The first three steps relate to the issue of how to select a set of high-quality constituent markets, and the last two steps relate to the issue of the statistical techniques used to calculate a price. Specifically, the first step relates to how to quantify an exchange's trustworthiness and establish a set of trusted exchanges to be used in subsequent steps. The second step relates to how to generate a universe of candidate constituent markets that are eligible for consideration as constituent markets. The third step relates to how to select a unique set of high-quality constituent markets for each digital asset. The fourth step relates to how to apply statistical techniques to the input data collected from the constituent markets to calculate a price. And the fifth step relates to how to calculate a confidence interval reflecting the uncertainty in the determination of the price.

I. Methodology Discussion: Terminology

32. I use the terms "market" and "spot market," which I define more precisely here. Spot markets refer to a specific pairing of two assets, also known as a trading pair, listed on a specific exchange. The assets can be a digital asset or fiat currency, and the spot market allows buyers and sellers to exchange one asset for another asset. For example, Coinbase's BTC-USD spot market represents the trading pair for Bitcoin ("BTC") and U.S. dollars ("USD") on Coinbase. In this spot market, Bitcoin represents the base asset and U.S. dollars represents the quote asset, and by convention, volume is reported in units of the base asset and prices are

reported in units of the quote asset.

33. I also employ the term "digital asset," which I further define here, as my methodology involves distinct treatment for specific types of digital assets. However, each of the 428 digital assets identified in the scope of my assignment are spot assets and stablecoins. Spot assets are any digital asset that represents native units of a cryptocurrency. This category includes several highly recognized cryptocurrencies such as Bitcoin and Ethereum.

II. Methodology Discussion: Identification of Trusted Exchanges

34. As discussed above, trading in cryptocurrencies can occur at several hundred centralized or decentralized exchanges. The process of selecting constituent markets for calculating the price of a given cryptocurrency becomes highly challenging due to the large number of eligible exchanges. The difficulty is further compounded by the fact that some cryptocurrency exchanges engage in deceptive practices to manipulate their reported trading activity, such as facilitating or engaging in trades between the same party to artificially boost price, liquidity or interest (known as wash trading).

35. To deal with this issue, I relied upon a framework used at Coin Metrics to assess exchanges using several criteria that represent the fundamental properties of exchange trustworthiness: transparency, resilience & security, data quality, regulatory compliance, and API quality ("Coin Metrics' Trusted Exchange Framework"). The criteria examine public information about an exchange such as incident history, financial statements, and license disclosure as well as market activity that can be derived from an exchange's data.

36. The Coin Metrics Trusted Exchange Framework was developed after a comprehensive literature review to identify techniques in evaluating exchanges, including the extensive research in detecting wash trading, fake volume, and fraud in both traditional financial markets and in the digital assets industry. The framework also makes use of Coin Metrics'

unique experience of maintaining its data collection system for over 40 exchanges over the past five years, which involves extensive interaction with exchanges' APIs and regular evaluations of data quality issues and interruptions in service. The full text of the Coin Metrics Trusted Exchange Framework is included as Appendix B to this declaration.

37. One of the categories that is given a high weight in the framework is an exchange's data quality. This category utilizes several established techniques in the literature that have been used to identify fake volume on an exchange: the distribution of leading digits and fitting against Benford's Law, quantifying cross-correlation of volume across markets, examining the distribution of buy/sell flag permutations on trade sequences, examining the distribution of trade sizes, an analysis of lead/lag of asset prices to determine where price discovery occurs, and an analysis of pricing anomalies. These techniques analyze certain elements of a market's trading activity. Prior research on these techniques indicates that data produced by natural and legitimate trading activity exhibits a certain distribution or pattern in the data that is different from data produced by artificial and manipulated trading activity.

38. The Coin Metrics Trusted Exchange Framework assigns a rating to an exchange for each category, ranging from A to D. A rating of A indicates that the exchange excels in most or all of the factors assessed, and a rating of D indicates that the exchange scores poorly across most of the factors assessed. An exchange with a score of B or above in the data quality category qualifies an exchange to be a part of Coin Metrics' "trusted volume" universe, an important designation that is used to select high-quality constituent exchanges for the calculation of Coin Metrics' prices, indexes, metrics, and other data products.

39. For my assignment, I use identical criteria as described above to identify the set of trusted exchanges to be used in subsequent steps. According to the Coin Metrics Trusted

Exchange Framework, these exchanges are Binance, Binance.US, Bitfinex, Bitstamp, Bittrex, Bullish, Bybit, Coinbase, Crypto.com, Gate.io, Gemini, HitBTC, Huobi, itBit, Kraken, KuCoin, LMAX, and OKEx. I also use the overall numerical score given to each exchange as reported by the framework in subsequent steps.

40. I also identify a set of low-rated exchanges to be used in subsequent steps. These exchanges consist of exchanges which have a score lower than B in the data quality category. According to the Trusted Exchange Framework, these exchanges are BitFlyer, Bibox, CEX.IO, LBank, MEXC, Poloniex, Upbit, and ZB.com.

III. Methodology Discussion: Generation of Candidate Markets for Spot Assets

41. During my review of the data, I detected significant spreads between prices on FTX and prices on the trusted exchanges during the time window immediately preceding and at the Petition Time. Several factors may have contributed to these divergences, such as market participants factoring in FTX's increasing insolvency risk as information about its financial instability spread, challenges in executing arbitrage efficiently, and the specific timing of FTX suspending withdrawals for certain spot assets.

42. For each of the FTX digital assets, I generate a unique set of candidate markets which are eligible for evaluation to be selected as a constituent market. Due to the phenomenon described above, the logic that I use to generate candidate markets is based on the principle of preferring to select markets on the trusted exchanges, which do not include FTX, then preferring to select markets on the low-rated exchanges if a particular digital asset does not trade on the trusted exchanges, and minimizing the selection of markets on FTX, to the extent possible.

43. For a given FTX digital asset, this means that if the identical digital asset is listed on one or more trusted exchanges, the candidate markets are selected from the trusted exchanges. If the digital asset does not trade on trusted exchanges, then candidate markets are selected from

the low-rated exchanges. Only when a given digital asset is exclusive to FTX are FTX markets selected.

44. The majority of spot assets that were listed on FTX were also listed on a large number of the trusted exchanges. Consequently, for the majority of spot assets, I selected markets from the trusted exchanges to serve as the candidate markets, given the fungibility of spot markets. However, for the small number of spot assets that were exclusively available on FTX, I selected markets from FTX to serve as the candidate markets. I use the following logic to generate the candidate markets:

- If the digital asset is Bitcoin or Ethereum, the candidate markets are spot markets on the trusted exchanges where the base asset is Bitcoin or Ethereum, respectively, and the quote asset is U.S. dollars.

- If the digital asset is Tether, the candidate markets are (1) spot markets on the trusted exchanges where the base asset is Tether and the quote asset is U.S. dollars, and (2) spot markets on the trusted exchanges where the base asset is Bitcoin or Ethereum and the quote asset is Tether. The logic to generate candidate markets for Tether differs from other spot assets because market convention sets Tether as the quote asset for the majority of its active markets.[4]

- If the digital asset is a spot asset that is not a stablecoin, the candidate markets are spot markets on the trusted exchanges where the base asset is the digital asset and the quote asset is either U.S. dollars, Bitcoin, Ethereum, Tether, or USD Coin. A stablecoin is a cryptocurrency asset that is designed to maintain a stable value by pegging its value to a fiat currency, such as the U.S. Dollar.

- If the digital asset is a spot asset that is a stablecoin, the candidate markets are (1) spot markets on the trusted exchanges where the base asset is the stablecoin and the quote asset is U.S. dollars, Tether, or USD Coin, and (2) spot markets on the trusted exchanges where the base asset is Bitcoin or Ethereum and the quote asset is the stablecoin. The logic to

[4] The logic to generate candidate markets for Tether differs from other spot assets because the markets with the most trading activity are generally markets where Tether is the quote asset, rather than the base asset. For example, for a given exchange, an exchange's Bitcoin-Tether market will generally have volumes that are several magnitudes larger than an exchange's Tether-U.S. Dollar market. Furthermore, some exchanges may only list a Bitcoin-Tether market and will not list a Tether-U.S. Dollar market. By including these markets, we can consider the highest volume markets with the most robust data.

generate candidate markets for stablecoins differs from other spot assets because market convention sets stablecoins as the quote asset for the majority of its active markets.[5]

- To be considered a candidate market, the market must have been active as of the Petition Time.

- If the rules described above result in zero candidate markets for a given digital asset, the rules are executed in order again, except that low-rated exchanges are added to the set of trusted exchanges.

- If the rules described above result in zero candidate markets for a given digital asset, the rules are executed in order again, except that FTX is added to the set of trusted exchanges. This contingency rule is necessary because for a small number of spot assets, FTX was the only exchange that listed the asset.

- If the rules described above result in zero candidate markets for a given digital asset, the rules are executed in order again, except that Liquid is added to the set of trusted exchanges. This contingency rule is necessary because for a small number of spot assets, Liquid was the only exchange that listed the asset.

- If the rules described above result in zero candidate markets for a given digital asset, the rules are executed in order again, except that the requirement that the market must have been active as of the Petition Time is removed.

IV. Methodology Discussion: Selection of Constituent Markets

45. For each of the FTX digital assets, I select a unique set of constituent markets from the identified candidate markets from which input data is collected for the calculation of the price. I use the following logic to select the constituent markets for each of the FTX digital assets:

- For each candidate market, I calculate the last price in U.S. dollars using the last trade preceding the Petition Time (the "<u>Last Price</u>"). If the constituent market is quoted in an asset other than U.S. dollars, the price is converted to U.S. dollars using the Coin Metrics Reference Rate, one of the prices contained within the Coin Metrics Prices.

[5] The logic to generate candidate markets for stablecoins differs from other spot assets for the same reason as Tether, described in the footnote above.

- For each candidate market, I calculate the average hourly volume in U.S. dollars for the 24 hours prior to the Petition Time. If the constituent market is quoted in an asset other than U.S. dollars, the volume is converted to U.S. dollars using the Coin Metrics Reference Rate.

- For each candidate market, I exclude the candidate market if it has a volume market share of less than 1 percent, where the volume market share is calculated as the average hourly volume in U.S. dollars described above divided by the sum of the average hourly volume in U.S. dollars of all candidate markets for the given digital asset.

- For each candidate market, I exclude the candidate market if the Last Price exceeds 10 percent from the median Last Price, where the median is calculated using the Last Price for all candidate markets for the given digital asset.

- I sort the candidate markets by quote asset using the following order: U.S. dollars, Bitcoin, Ethereum, USD Coin, and Tether. Within each grouping of quote asset, I further sort, in descending order, the candidate markets by each such candidate market's exchange score from the Coin Metrics Trusted Exchange Framework.

- I select a candidate market as a constituent market if the candidate market meets the following criteria: (1) the candidate market is ranked within the top six according to the sorting described above, or (2) the candidate market is ranked within the top 10 according to the sorting described above, and the candidate market has a volume market share that exceeds 20 percent.

- If there are no candidate markets that meet these criteria, I select the constituent markets using expert judgment.

V. Methodology Discussion: Calculation of Price

46. The methodology I use to calculate the prices is identical to the methodology used to calculate the Coin Metrics Reference Rate, one of the prices contained within the Coin Metrics Prices. The calculation methodology is described below:

- Calculate the volume denominated in units of the given asset from observable transactions that occurred over the trailing 60 minutes for each of the constituent markets.

- Calculate the volume weight for each of the constituent markets by dividing the volume figure for each of the constituent markets by the

total volume across all constituent markets. The resulting figure is referred to as the volume weight.

- Convert the trade price of all observable transactions over the trailing 60 minutes for each of the constituent markets to U.S. dollars if necessary using the Coin Metrics Reference Rate calculated for Bitcoin (BTC), Ethereum (ETH), USD Coin (USDC), or Tether (USDT).

- Calculate the inverse variance of the trade price converted to U.S. dollars for each of the constituent markets using the population mean in the calculation of variance, where the population mean is defined as the mean price of all trades from constituent markets over the trailing 60 minutes. If a constituent market has an infinite or undefined inverse price variance, the inverse price variance for that constituent market is set to zero, unless there is only one market with previous trades and those trades have a single price. In the case where all available trades have the same price and occur on the same market, that market's inverse weight is set to 1.0. Otherwise, calculate the inverse price variance weight for each of the constituent markets by dividing the inverse price variance by the total inverse price variance across all constituent markets. The resulting figure is referred to as the inverse price variance weight.

- Calculate the final weight for each of the constituent markets by taking a mean of the volume weight and the inverse price variance weight.

- Extract the most recent observable transaction from each of the constituent markets. Convert the trade price of the most recent observable transactions to U.S. dollars if necessary using the Coin Metrics Reference Rate calculated for Bitcoin (BTC), Ethereum (ETH), USD Coin (USDC), or Tether (USDT).

- Calculate the weighted median price of the most recent observable transactions using the trades prices obtained in step 5 and the final weights calculated in step 4. The weighted median price is calculated by ordering the transactions from lowest to highest price, and identifying the price associated with the trades at the 50th percentile of final weight. In the case of two observations which both lie at the 50th percentile of final weight, we utilize the lower weighted median. The resulting figure is the calculated price for the given digital asset

47. The following contingency rules are followed to address situations where data is delayed, missing, or unavailable due to periods of illiquidity, extraordinary market

circumstances, or outside factors beyond the control of Coin Metrics.

- If observable transactions from a constituent market are unable to be collected due to technical problems specific to the constituent market's exchange during the calculation of a price, the observable transactions from the constituent market are not included in the calculation of the specific instance of the given price.

- If no observable transactions from constituent markets exist during the trailing 60 minutes, the value of the price will be determined to equal the value calculated during the previous second.

VI. Methodology Discussion: Calculation of Confidence Interval

48. For each of the digital assets, I calculate a confidence interval to obtain a measure of confidence or, inversely, the uncertainty of the prices calculated in this assignment. Market pricing is an inherently unpredictable process where many unknown factors can influence the price and where we often see trades for the same digital asset at the exact same time with differing prices.

49. The confidence interval is intended to estimate the range in prices within which I expect the true price of the digital asset to be within. I calculate the confidence interval at the 95 percent confidence level.

50. For each of the FTX digital assets, I use executed trades from constituent markets for the 10 minute period preceding the Petition Time to calculate the percent change in prices from adjacent trades. The digital assets are grouped by the number of trades available, and the 95th percentile of the observed change in prices from adjacent trades, within a group, is used as the minimum confidence interval for all digital assets with a similar number of trades.

51. I have taken the following approach to estimating a confidence interval for each digital asset:

- Using digital assets for which I can calculate a U.S. dollar volume, I extract trades from constituent markets in the 10 minute period

preceding the Petition Time, ordered by time, grouping trades from all constituent markets of an digital asset together.

- I filter out digital assets which have 10 trades or less and $100 or less in U.S. dollar trade volume during the 10 minute period. I only exclude digital assets that fail to meet both criteria. I also filter out digital assets with less than 3 trades during the 10 minute period regardless of its U.S. dollar trade volume during the 10 minute period.

- For each trade of each remaining digital asset, I calculate the percentage change in the price in U.S. dollars between the trade and the adjacent trade before it.

- I calculate the squared value of the percentage change in price described in the preceding step, weight the pair of trades by the average U.S. dollar volume of the two trades, sum the weighted differences, and calculate the square root of the total.

  The resulting figure is a measure of the typical size of changes in price between adjacent trades. I refer to this term as the root mean squared difference or "RMSD."

  Mathematically, The RMSD is given by the following formula for N trades, each with prices $p_i = [p_1, p_2, \ldots, p_N]$and U.S. dollar volumes $v_i = [v_1, v_2, \ldots, v_N]$:

$$RMSD = \sqrt{\sum_{i=2}^{N} \left(w_i \cdot \left(\frac{p_i - p_{i-1}}{p_i} \right)^2 \right) / \sum_{i=2}^{N} w_i}$$

  where,

  $w_i = (v_i + v_{i-1})/2$ is the weight of price p_i

- The digital assets are then grouped into bins determined by how many trades exist during the 10 minute period. The bins are chosen so that each bin is large enough to contain several digital assets, but granular enough to distinguish digital assets with few trades (e.g. 10 or less) from those with many trades.

  In each bin, I calculate the 95th quantile of the RMSD of the digital assets, which represents an upper bound on the size of price differences. I find the largest RMSD values of each band are roughly half of the RMSD before it. The count column in the table below represents how many digital assets fall in each band.

Trade Count Bin	RMSD (95th Quantile)	Count
(2.0, 10.0]	0.103681	12
(10.0, 50.0]	0.063939	18
(50.0, 100.0]	0.031465	19
(100.0, 500.0]	0.014476	62
(500.0, 1000.0]	0.007280	39
(1000.0, 10000.0]	0.003351	57
(10000.0, 1000000.0]	0.001929	31

- Because digital assets with less than 2 trades contain too few observations to calculate a RMSD at the 95th quantile, I extrapolate the change in RMSD at the 95th quantile between adjacent bins to estimate the RMSD at the 95th quantile for the bin with 0 to 2 trades. I extrapolate using the equation below:

$$q95([0,2]) = \frac{q95([2,10])}{q95([10,50])} = \frac{q95([0,2])}{q95([2,10])} = 0.168124$$

- Finally, each digital asset's confidence interval is calculated as its price plus or minus its price multiplied by the larger of the digital asset's RMSD or the RMSD at the 95th percentile in its bin. This means that for most digital assets, the confidence interval used will be calculated from values in the table above, but for the most volatile digital assets, the digital asset's RMSD will be used to calculate the confidence interval.

VII. Results

52. The price and confidence interval for the 428 FTX digital assets identified in the scope of my assignment are included in Appendix A to this declaration.

I declare under penalty of perjury that the foregoing is true and correct.

Dated: December 27, 2023

Respectfully submitted,

Kevin Lu

Kevin Lu
Director of Data Science & Product
Coin Metrics

Appendix A

Prices and Confidence Intervals for FTX Digital Assets

Ticker	Price	Confidence Interval
1INCH	0.5506265	0.0039938
AAVE	63.9206190	0.2129413
AGLD	0.2463000	0.0035654
AKRO	0.0026846	0.0000845
ALCX	17.5644480	0.2542582
ALEPH	0.0634082	0.0019951
ALGO	0.2959040	0.0009858
ALICE	1.1828905	0.0085797
ALPHA	0.0912154	0.0013204
AMPL	0.9668414	0.0304217
ANC	0.0531424	0.0003855
APE	3.1755724	0.0061343
APT	4.7424485	0.0091611
ASD	0.0667762	0.0112694
ATLAS	0.0029998	0.0001911
ATOM	11.5991618	0.0224064
AUDIO	0.1566829	0.0011364
AURY	0.5119689	0.0326112
AVAX	14.1912756	0.0274137
AXS	6.8561913	0.0228403
BADGER	2.6147338	0.0378502
BAL	5.2393950	0.0758441
BAND	2.2614453	0.0075336
BAO	0.0001056	0.0000109
BAR	3.9021409	0.0564863
BAT	0.2526885	0.0018328
BCH	102.2131116	0.3405066
BCHA	0.0000300	0.0000031
BICO	0.2864203	0.0041461
BIT	0.3165593	0.0022961
BLT	0.0418393	0.0070609
BNB	286.5200580	0.5534785
BNT	0.3792324	0.0054897
BOBA	0.2207532	0.0028540
BRZ	0.1562968	0.0263771
BTC	16871.6300000	32.5913800
BTT	0.0000007	0.0000000
BUSD	0.9999760	0.0019317
C98	0.2040890	0.0014803
CEL	0.6219474	0.0045111
CHR	0.1122728	0.0008143
CHZ	0.2197552	0.0004245

CITY	4.6107138	0.0667434
CLV	0.0598594	0.0008665
COMP	37.9232400	0.2750641
CONV	0.0005770	0.0000182
COPE	0.0063050	0.0006537
CQT	0.0874388	0.0012657
CREAM	6.8911210	0.2168294
CRO	0.0875500	0.0002917
CRV	0.6516809	0.0021710
CUSDT	0.0218002	0.0036791
CVC	0.0911835	0.0013199
CVX	4.0218594	0.0291713
DAI	0.9997000	0.0033303
DAWN	0.7468876	0.1260469
DENT	0.0006846	0.0000099
DFL	0.0011693	0.0001212
DMG	0.0091086	0.0005802
DODO	0.1128715	0.0016339
DOGE	0.0828523	0.0001600
DOT	5.6705792	0.0109540
DYDX	1.9869782	0.0038383
EDEN	0.0804372	0.0025310
EMB	0.0192000	0.0032402
ENJ	0.3445027	0.0024987
ENS	12.2252550	0.0407265
ETH	1258.8400000	2.4317350
ETHW	4.1505988	0.0138271
EUL	6.1800531	0.0205879
EUROC	1.0265000	0.1732351
EURT	1.0248257	0.0652789
FIDA	0.2303338	0.0033342
FRONT	0.1701556	0.0024631
FTM	0.1917738	0.0006389
FTT	2.6876599	0.0051918
FXS	5.1236807	0.0741690
GAL	1.5049689	0.0050136
GALA	0.0308076	0.0001026
GALFAN	1.6386832	0.0054590
GARI	0.0375240	0.0005432
GENE	1.7487763	0.1813152
GMT	0.3851205	0.0012830
GMX	32.5640874	0.2361932
GODS	0.2403136	0.0047847

GOG	0.1030913	0.0014923
GRT	0.0644695	0.0004676
GST	0.0259475	0.0003756
GT	3.8283511	0.0127535
HBB	0.0645693	0.0041129
HGET	0.3483396	0.0361163
HMT	0.0503377	0.0032064
HNT	2.8245828	0.0408879
HOLY	1.2800000	0.1327119
HT	5.6096533	0.0186877
HUM	0.0753202	0.0127113
HXRO	0.0527828	0.0089078
IMX	0.4485000	0.0014941
INDI	0.1317318	0.0021630
INTER	2.2220025	0.2303798
IP3	0.2929130	0.0494328
JET	0.0754000	0.0127247
JOE	0.1576808	0.0022825
JST	0.0226663	0.0000755
KIN	0.0000092	0.0000010
KNC	0.5928001	0.0042997
LDO	1.1764306	0.0039191
LEO	4.0838828	0.0591172
LINA	0.0061216	0.0000886
LINK	6.7932499	0.0131227
LOOKS	0.1468043	0.0010648
LRC	0.2596744	0.0008651
LTC	60.6106000	0.2019145
LUA	0.0127744	0.0013245
LUNA2	1.6770056	0.0032395
LUNC	0.0001877	0.0000006
MAGIC	0.2734465	0.0174179
MANA	0.4919000	0.0016387
MAPS	0.0985383	0.0102166
MASK	3.3033138	0.0063811
MATH	0.1112000	0.0016097
MATIC	1.0265325	0.0019830
MBS	0.0898182	0.0028261
MCB	4.3032898	0.2741091
MEDIA	4.7500000	0.8016238
MER	0.0078455	0.0013240
MKR	780.1942307	11.2938790
MNGO	0.0123275	0.0020804

MOB	0.6213997	0.0089952
MPLX	0.0635720	0.0002118
MSOL	16.0000000	1.0191610
MTA	0.0388458	0.0040276
MTL	0.6666573	0.0022209
MYC	0.0304800	0.0051439
NEAR	2.1160000	0.0070491
NEXO	0.7285254	0.0024270
OKB	19.0903594	0.0635965
OMG	1.2318000	0.0178312
ORBS	0.0246122	0.0002687
ORCA	0.4958000	0.0315813
PAXG	1753.4508600	25.3824766
PEOPLE	0.0320352	0.0000619
PERP	0.4211518	0.0014030
POLIS	0.2158631	0.0223809
PORT	0.0289414	0.0030007
PRISM	0.0043781	0.0004539
PROM	4.3251889	0.0144087
PSG	5.8781611	0.0850907
PSY	0.0233829	0.0024244
PTU	0.8981820	0.0572120
PUNDIX	0.3642664	0.0012135
QI	0.0063072	0.0001985
RAMP	0.0287482	0.0048516
RAY	0.2532873	0.0018371
REAL	0.1050873	0.0066938
REEF	0.0034151	0.0000114
REN	0.0824000	0.0005977
RNDR	0.5381211	0.0017927
ROOK	14.2065247	1.4729491
RSR	0.0042055	0.0000305
RUNE	1.1476770	0.0038233
SAND	0.6218413	0.0020716
SECO	1.0001000	0.1036915
SHIB	0.0000098	0.0000000
SKL	0.0269854	0.0003906
SLND	0.3878150	0.0402091
SLP	0.0025947	0.0000376
SLRS	0.0039720	0.0004118
SNX	1.8312933	0.0132827
SNY	0.0975026	0.0101092
SOL	16.2471144	0.0317575

SOS	0.0000002	0.0000000
SPA	0.0069230	0.0001002
SPELL	0.0006802	0.0000098
SRM	0.3722465	0.0023922
STARS	0.0325200	0.0054882
STEP	0.0080138	0.0005105
STETH	1252.4649000	129.8570272
STG	0.3901143	0.0012996
STMX	0.0048053	0.0001512
STORJ	0.3129665	0.0045304
STSOL	18.6929248	3.1546722
SUN	0.0054091	0.0000783
SUSHI	1.2374952	0.0041225
SWEAT	0.0143510	0.0002077
SXP	0.2289366	0.0016605
SYN	0.5850000	0.0184070
TAPT	5.3425111	0.9016177
TLM	0.0157681	0.0001144
TOMO	0.2907561	0.0042089
TONCOIN	1.5482817	0.0051579
TRU	0.0345301	0.0004998
TRX	0.0556107	0.0001074
TRYB	0.0509070	0.0032426
TULIP	1.6566468	0.1055244
TUSD	0.9978553	0.0144447
UBXT	0.0015159	0.0000219
UMEE	0.0083132	0.0001203
UNI	5.7583446	0.0191830
USDC	1.0000000	0.0019317
USDP	0.9990984	0.1686107
USDT	0.9975910	0.0019271
USTC	0.0239415	0.0000798
VGX	0.2295354	0.0033227
WAVES	2.3262914	0.0077497
WAXL	0.6885064	0.0049939
WBTC	16864.9139190	530.6550925
WFLOW	15.0000000	0.9554634
WRX	0.1547882	0.0022407
XAUT	1757.4000000	55.2966510
XPLA	0.2911263	0.0491313
XRP	0.3762385	0.0007268
YFI	6389.0679600	46.3410642
YFII	1903.5322345	6.3413123

YGG	0.2386170	0.0017307
ZRX	0.1830295	0.0026495
1WO	0.0746005	0.0125898
ABBC	0.1642675	0.0051687
ABEY	0.6159533	0.0089164
ADH	0.0004097	0.0000691
ALBT	0.0478631	0.0006929
ALX	0.0024237	0.0004090
AMLT	0.0005755	0.0000971
AMN	0.0006383	0.0001077
ANCT	0.1000000	0.0168763
ANW	0.0007285	0.0000755
ARV	0.0001056	0.0000015
ASM	0.0160900	0.0002329
BAAS	0.0005289	0.0000893
BERRY	0.0006108	0.0000048
BFC	0.0738605	0.0023240
BMC	0.0014999	0.0002531
BRC	0.0034500	0.0005822
BSV	38.2825128	0.5541672
BTCV	2.5096431	0.4235346
BTRN	0.0006326	0.0001068
CAN	0.0004910	0.0000016
CAPS	0.0086027	0.0008919
CIM	0.0051254	0.0008650
CLRX	0.1999800	0.0337492
CMCT	0.0000359	0.0000061
COT	0.0384302	0.0064856
CPH	0.0263766	0.0016801
CRPT	0.0782117	0.0011322
CRT	0.1100772	0.0114129
CTK	0.7734423	0.0111961
CTX	2.2718017	0.0100074
CUDOS	0.0034291	0.0000249
DACS	0.0007433	0.0001254
DAG	0.0491076	0.0007109
DASH	35.5184641	0.2576218
DEXA	0.0000213	0.0000022
DIA	0.2999928	0.0043426
DRG	0.0000920	0.0000155
DS	0.0002176	0.0000367
EARTH	0.0001708	0.0000288
ECH	0.0000903	0.0000152

EGLD	45.2084940	0.3279054
ELY	0.0135584	0.0022882
EOS	0.9051769	0.0030155
ETC	21.0673578	0.0701825
ETN	0.0023543	0.0000741
EWT	3.4440290	0.0249802
EZT	0.0048603	0.0008202
FCT	0.5845263	0.0986464
FDX	0.0003616	0.0000610
FIO	0.0300062	0.0001000
FLEX	1.9130945	0.3228594
FLIXX	0.0006384	0.0001077
FLOKI	0.0000078	0.0000001
FTX	0.0036174	0.0006105
FUSE	0.0678327	0.0043208
GATE	0.0043444	0.0007332
GEN	0.2700000	0.0455660
GET	0.7966969	0.1344529
GOM2	0.0045210	0.0007630
GRNC	0.1196829	0.0201980
GUSD	0.9978045	0.1034535
GXT	0.0015052	0.0001561
GYEN	0.0071050	0.0004526
GZE	0.0077204	0.0013029
GZIL	5.8000000	0.9788248
HBAR	0.0471047	0.0003417
HEART	0.0044909	0.0002861
HERO	0.0040153	0.0000581
HOT	0.0007091	0.0001197
HUSD	0.9917954	0.1673783
HYDRO	0.0028263	0.0004770
IDH	0.0007901	0.0001333
IDRT	0.0000680	0.0000115
ILK	0.0080784	0.0013633
IND	0.0034088	0.0005753
IPSX	0.0001920	0.0000324
KLAY	0.1792372	0.0013000
KMD	0.1879196	0.0027203
KRL	0.2927662	0.0092119
KSM	25.9275204	0.1880570
LALA	0.0020512	0.0003462
LBL	0.0042605	0.0007190
LCX	0.0482000	0.0030702

LDC	0.0000543	0.0000092
LIKE	0.0041486	0.0000262
LND	0.0003625	0.0000612
LPT	7.5747441	0.1096499
LTX	0.3110735	0.0097879
MARX	0.0089775	0.0015151
MGO	0.0238830	0.0040306
MIMO	0.0142254	0.0024007
MIOTA	0.2228489	0.0016164
MITX	0.0038093	0.0001199
MNR	0.0006801	0.0001148
MRK	0.0007818	0.0001319
MT	0.0001984	0.0000206
MTC	0.1037970	0.0175171
MVL	0.0034930	0.0002225
NDAU	15.5416983	0.2249774
NEO	6.7363650	0.0488601
NII	0.0003073	0.0000319
NPLC	0.0000066	0.0000011
NPXS	0.0073805	0.0012456
NUC	0.3840925	0.0648206
NUM	0.0403188	0.0001343
OAX	0.0916656	0.0013269
OXY	0.0314364	0.0020024
PAR	1.0258451	0.1731246
PCI	0.2461043	0.0077437
PERI	0.0761159	0.0078918
PLA	0.1956041	0.0066619
PLG	0.0004461	0.0000463
PLI	0.0530000	0.0033760
PMA	0.0000183	0.0000031
POWR	0.1392196	0.0020153
PPP	0.0063995	0.0010800
QASH	0.0204863	0.0021240
QBZ	0.0001998	0.0000337
QTUM	2.1935600	0.0159103
RBLX	0.0311088	0.0052500
RBTC	19560.9559000	3301.1636132
REDI	0.0009310	0.0001571
REP	5.1596083	0.1623473
RFOX	0.0062973	0.0004011
RIF	0.0387725	0.0012200
ROOBEE	0.0009154	0.0000335

RSV	0.9969920	0.1033693
SAL	0.0021860	0.0003689
SER	0.0105808	0.0017856
SGN	0.0031750	0.0005358
SHP	0.0004982	0.0000841
SHPING	0.0049610	0.0003160
SHX	0.0005588	0.0000356
SIX	0.0434320	0.0073297
SNIP	0.0000535	0.0000090
SOLO	0.2279210	0.0016821
SPDR	0.0001258	0.0000212
SPHTX	0.0001542	0.0000260
SRX	0.0148499	0.0015397
SSX	0.0149817	0.0015533
STAC	0.0000686	0.0000116
STX	0.2255435	0.0032649
SUN_OLD	0.0054091	0.0000783
SUPER	0.1040800	0.0015066
SYL	0.0009001	0.0001519
TEM	0.1417853	0.0239281
TFT	0.0381828	0.0064438
THRT	0.0016469	0.0002779
THX	0.1282545	0.0216446
TMTG	0.0000923	0.0000059
TPAY	0.0020951	0.0003536
TPT	0.0062374	0.0006467
TRL	0.0225543	0.0014367
TTU	0.0191313	0.0032287
UBT	0.1414271	0.0238676
UBTC	0.4545450	0.0767103
UKG	0.0108682	0.0018341
USDS	1.0999000	0.1856223
VFOX	0.0941208	0.0158841
VI	0.0051000	0.0008607
VIDY	0.0000838	0.0000053
VIDYX	0.0006897	0.0000715
VIO	0.0120884	0.0020401
VOY	0.0019107	0.0003225
VUU	0.0008551	0.0001443
VZT	0.0095366	0.0016094
WABI	0.0624643	0.0009042
WEMIX	1.4722348	0.0213117
WIN	0.0000949	0.0000007

WLO	0.0000441	0.0000074
XCF	0.0020557	0.0003469
XDC	0.0271151	0.0003925
XEM	0.0329337	0.0004767
XES	0.0082220	0.0013876
XKI	0.0480000	0.0081006
XLM	0.0938490	0.0003126
XMR	125.5384776	1.8172608
XNK	0.0004719	0.0000796
XPR	0.0019111	0.0000277
XPT	0.0000400	0.0000068
XSGD	0.7082000	0.1195179
XTZ	1.0702000	0.0154919
ZCO	0.0012193	0.0002058
ZEC	38.3224320	0.5547451
ZIL	0.0224346	0.0001627
ZPR	0.0000183	0.0000031
ZUSD	0.9794021	0.1652867
ZWAP	1.6400000	0.2767712
ADA	0.3497920	0.0006757
AR	9.5507643	0.1292157
BEAM	0.1138695	0.0016483
BIFI	0.0068162	0.0004342
CRE	0.0028662	0.0002972
FIL	4.3670766	0.0145482
FRAX	0.9880101	0.1024380
GLMR	0.3835063	0.0012776
IXT	0.0024147	0.0004075
KNCL	0.5928001	0.0042997
LOOM	0.0439616	0.0006364
MAID	0.1184386	0.0199880
MITH	0.0145306	0.0002103
ONT	0.1763431	0.0012790
PAI	0.0002740	0.0000462
QKC	0.0078844	0.0001141
RENBTC	16476.6225011	2780.6425692
SAI	0.9924119	0.1674823
TON	1.1965831	0.2019388
VET	0.0211672	0.0000705
WOM	0.0302677	0.0009524
XNO	0.0083402	0.0000278
ZEN	10.1894779	0.0739061

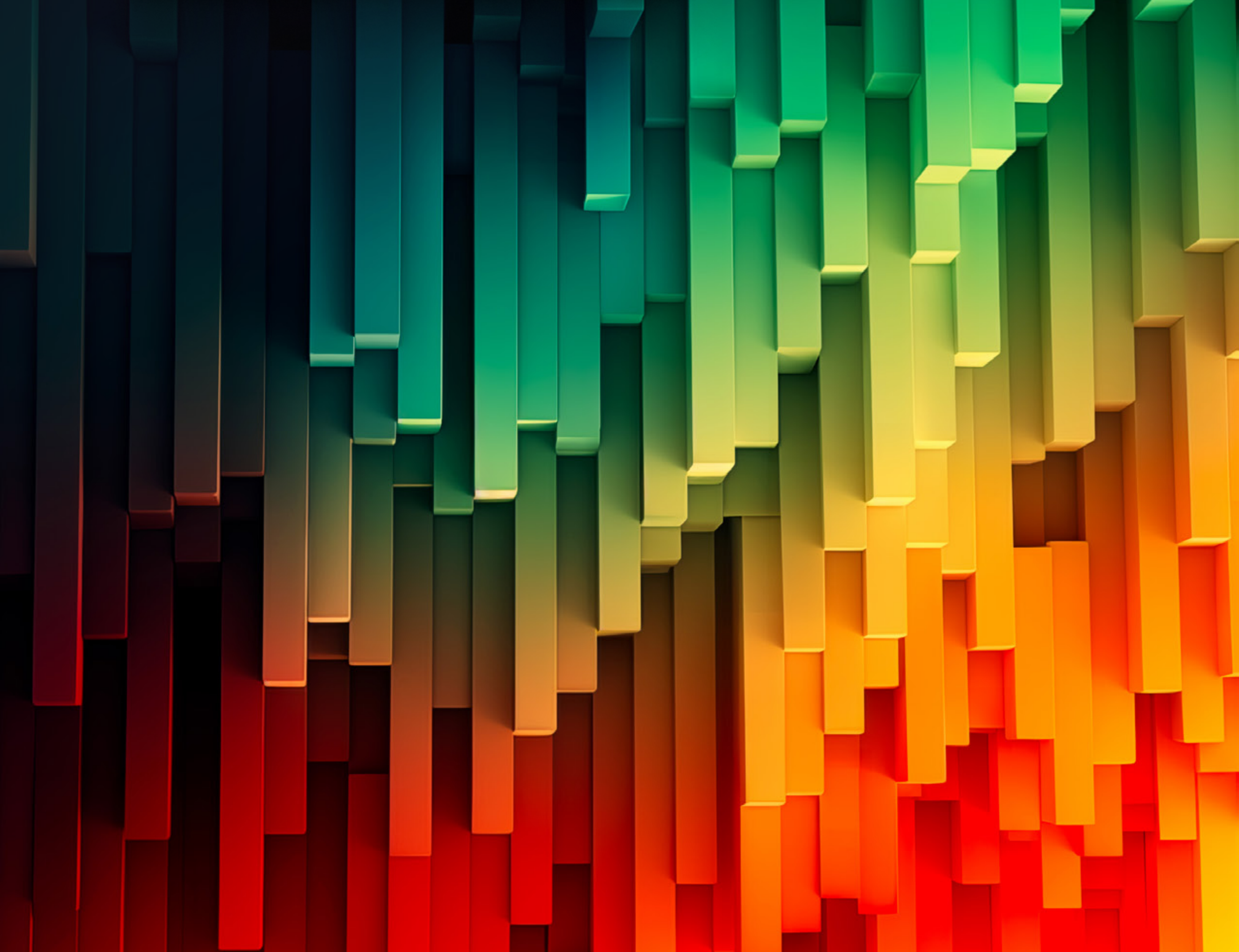
Appendix B

Coin Metrics Trusted Exchange Framework

COINMETRICS

TRUSTED EXCHANGE FRAMEWORK 2.1

By Victor Ramirez, Dorian Kandi, Kevin Lu,
Christian Brazell, and the Coin Metrics Team



INTRODUCTION

Centralized exchanges are a vital part of the crypto ecosystem, serving as the primary interface to the blockchain for a significant percentage of market participants. Yet, exchanges vary widely in quality across several use-cases, whether as custodial platforms, as data sources, or as entities for executing programmatic actions.

The Coin Metrics' Trusted Exchange Framework thus aims to quantitatively assess exchanges to promote transparency, innovation, and trust for the industry and its users. The common usage patterns for an exchange are translated to criteria that define the fundamental properties of exchange trustworthiness: transparency, resilience & security, data quality, regulatory compliance, and API quality. The criteria sources public information about an exchange such as incident history, financial statements, and license disclosure as well as market activity that can be derived from exchange data.

During the course of our research, we conducted a comprehensive literature review to identify prior techniques in evaluating exchanges, including the extensive research in detecting wash trading, fake volume, and fraud. Several of these techniques are included in our framework. We also made use of Coin Metrics' unique experience of maintaining our market data collection system for over 40 exchanges over the past five years, which involves extensive interaction with exchanges' APIs and regular evaluations of data quality issues and interruptions in service. Our framework contributes to the literature by utilizing a primarily quantitative approach in calculating exchange features (keeping subjective determinations to a minimum) and presenting the most complete collection of all facets of exchange trustworthiness to date.

Coin Metrics utilizes the output from our Trusted Exchange Framework to select high-quality constituent exchanges in our prices, indexes, and metrics.

RELEASE NOTES

2.1 (October 2023)

In response to feedback to the first iteration of the Trusted Exchange Framework V2, several improvements were made to create a simpler and easier to interpret framework. Below is a quick summary of what's new.

- Numeric scores have been translated into a letter grading scale for convenience. See Grading Scale.
- The Regulatory score was revamped to be significantly more reflective of how crypto exchanges are regulated globally. Exchanges are no longer penalized for not operating under the US if they serve their international customers in a manner that is deemed acceptable to regulators in reputable jurisdictions. The new score is more focused on the regulatory compliance framework rather than general compliance (security standards, which are now moved to Resilience & Security)
- Transparency and Resilience were broken out into their own separate scores to make for more mutually exhaustive groupings.
- Infrastructure now refers to API Quality. New criteria such as rate limit assessments were added.

Conclusion

Although the notion of a "Trusted Exchange" is a bit of a misnomer and highly dependent on the context, the framework serves as a rough approximation of how to holistically evaluate exchanges based on the most important qualities it must have. As noted in the past, we highly encourage users to think closely about what context they may evaluate exchanges on, and apply that context with the evaluation criteria within the Framework in mind. Treat this framework more like a model; "All models are wrong, but some are useful".

Please note our **FAQ** for common questions regarding our framework.

2.0 (March 2023)

The original framework was primarily focused on quantifying the amount of fake volume per exchange. New techniques have since been developed that directly measure the footprints of fake volume using a wider variety of market data from the exchange. Additionally, the new framework expands beyond quantifying fake volume and into providing a more holistic assessment of an exchange's trustworthiness.

OVERALL RANKINGS

EXCHANGE	DATA QUALITY (SPOT)	TRANSPARENCY	RESILIENCE & SECURITY	REGULATORY COMPLIANCE	API QUALITY	GRADE
Kraken	A	A	A-	A	C-	A
Crypto.com	A	B	B-	A	B+	A
Bybit	A	B	A	A	D	A-
OKX	A	B	B	A	D	A-
Coinbase	A	C	C	A	A-	A-
Gemini	A	C+	B-	A	C-	A-
Huobi	A	C+	C+	A	C-	B+
CME	N/A	A	B	A	D	B+
Bitstamp	A	D	A	A	C	B
Itbit	A	D	A	A	C-	B
LMAX	A	C	A-	B	C	B
Binance	A	D	C	A	C	B
Bitfinex	A	C-	A-	B	C	B
BitMEX	N/A	A	A	C	C+	B-
Gate.io	A	B	B-	C	C-	B-
Kucoin	A	A-	C-	C	D	B-
Bitflyer	C	D	A	A	C-	B-
BitBank	N/A	D	A-	A	C-	B-
Bittrex	A	D	A	C	C-	C+
Deribit	N/A	A	D	C	A	C+
Binance.US	A	D	C	C	B+	C+
Bullish	B	D	A	B	C	C+
CEX.io	C	D	C+	B	C+	C
MexC	C	C+	B	C	D	C
HitBTC	A	D	D	D	A	C-
Upbit	D	C	C	C	D	C-
Poloniex	C	D	C	D	C	D
Bibox	C	D	C+	D	C-	D
LBank	C	D	C+	D	D	D

**Exchanges without sufficient data were not penalized for their data quality scores. They are however disqualified for being included in the trusted volume metric.*

Grading Scale

We translated the numeric scores into a letter grading scale for convenience. The table below illustrates how to interpret the resulting scores.

GRADE	INTERPRETATION
A- to A	These exchanges excel in most or all of the factors assessed. Exchanges in this tier often have the highest quality data and efficient markets relative to its peers.
B- to B+	These exchanges are generally of good quality across most of the factors assessed. Minor penalties in Data Quality, Regulatory Compliance, Transparency, and/or Resilience & Security keep exchanges in this tier from being in the A tier.
C- to C+	These exchanges are generally middle-of-the-road across most of the factors assessed. Some exchanges in this tier may have organic trading activity, but suffer from incomplete compliance and/or past minor security incident(s), and vice versa.
D	These exchanges score poorly across most of the factors assessed. Exchanges in this tier tend to not be compliant in major jurisdictions, have suffered major security incidents, and/or contain significant amounts of inorganic market activity.

Weights

Each category is scored across numerous subcategories (see next section) and normalized each to a max score of 1. These categories were then computed with a weighted average to create an overall score. The categories are weighted using the following values:

EXCHANGE TYPE	DATA QUALITY (SPOT)	TRANSPARENCY	RESILIENCE & SECURITY	REGULATORY COMPLIANCE	API QUALITY	TOTAL
Spot	30%	15%	15%	30%	10%	100%
Futures-Only*	0%	21.4%	21.4%	42.9%	14.3%	100%

**Futures-Only weights were derived by omitting spot data quality and proportionally distributing weights across the remaining categories. Exchanges with an N/A for Data Quality (Spot) are applied with the Futures-Only weighting.*

Note that the "true" value of the weights are relative to the context of how an exchange is being used. A custody-focused use-case looking to avert risk may downweight Data Quality and API Quality in favor of Transparency, Resilience & Security, and Regulatory Compliance. In contrast, a data-provider that relies on exchange APIs but does not hold assets in custody in exchanges may want to weigh these categories in the opposite direction. We publish the scores for each category so that users with unique use cases can make their own assessment if needed.

Each category is explained in depth in the next section along with a description of each feature used to evaluate exchange trustworthiness.

CATEGORIES

The Trusted Exchange Framework categorizes the major categories of exchange trustworthiness as: Data Quality, Regulatory Compliance, Transparency, Resilience & Security, and Technical Infrastructure / API Quality. These categories are broadly defined below.

Data Quality (Spot)

The Data Quality score assesses the confidence that an exchange's reported data is accurate. Exchanges are the primary source for market data metrics such as price and volume, yet exchange-reported data has historically been fabricated. Crypto exchanges are known to create "fake" or non-economic volume to attract users to its platform.

Estimates vary on how much of the reported volume is fake. Bitwise estimated in 2019 that 95% of volume reported by exchanges are fake by observing anomalous trade patterns.[2] Forbes estimated in 2022 that about 51% of bitcoin trading volume is fake by weighting likelihood of fake volume given regulatory and web usage patterns.[3] However, fake volume boiled down to a percent value is misleading because it depends on which exchanges are included in the calculation, the reported volume of each exchange, and the proportionality of volume that is fake. For example, if a well-behaved crypto exchange accurately reports $100M of volume in one day and an ill-behaved crypto exchange reports $1.9B of mostly fake volume in one day, then ~95% of the volume between those two exchanges is fake.

Fake volume is not evenly distributed across crypto exchanges. The variance in our data quality test results is strong evidence of this. Thus, we want to only include trustworthy exchanges and exclude exchanges whose volumes are shown to be mostly inorganic when calculating metrics such as total trading volume.

This category utilizes several techniques that have been used to identify fake volume on an exchange: the distribution of leading digits and fitting against Benford's Law, quantifying cross-correlation of volume across markets, examining the distribution of buy/sell flag permutations on trade sequences, examining the distribution of trade sizes, an analysis of lead/lag of asset prices to determine where price discovery occurs, and an analysis of pricing anomalies.

Trusted Volume

A score of **B** or above on the Data Quality category qualifies an exchange to be a part of our "trusted volume" universe, an important designation that is used to select high-quality constituent exchanges for the calculation of Coin Metrics' prices, indexes, metrics, and other data products. An exchange with this designation is determined to have *most* of its trading volumes to be organic.

Calculation Methodology

Data Sampling

All data was sourced from Coin Metrics Market Data Feed. Due to large amounts of transaction data that can accrue over time, it's unfeasible to apply all of these techniques across all transactions and markets for a long period of time. These techniques were instead applied on a synthetic 24 hour dataset randomly sampled across the most liquid markets across several time windows bounded by a time period of interest (e.g. Q3 2022-Q3 2023) to minimize sampling bias.

Scoring

Each feature is scored by how well an exchange's observed market data is distributed relative to a known ideal or expected value or distribution. Using a representative sample of market data for each exchange, a goodness-of-fit score is calculated against the expected distribution for a given feature. These scores are weighted by market volume and averaged to compute a composite score for each feature and exchange. For each feature, statistical tests are applied to rank exchanges relative to its peers. An exchange that deviates too far from the expected behavior for a given feature fails the test and is thus penalized.

Note that this score represents an estimated "confidence level" (not in the traditional statistical sense) of how likely most of an exchange's volume is representative of organic and informed market activity. An exchange that fails one test signals a moderate amount of confidence about the exchange's data quality, but does not rule out the possibility that most of the exchange's volume is organic due to the likelihood of false positives. An exchange that fails multiple tests signals a general lack of confidence in data quality. Similarly, an exchange with a perfect score signals a general confidence for data quality but does not imply that their data is 100% accurate. Thus, the score is not meant to be interpreted as a strict probability or proportion of data that is legitimate.

Subcategories

Leading Digit Distributions (Benford's Law)

An assessment of how well an exchange's trade patterns follow a natural order of leading digits where leading digits tend to be small, also known as Benford's Law. Benford's Law has been used to detect fraud in financial (such as trade amounts in traditional markets) and non-financial applications (such as elections) where the distributions of quantities of leading digits do not follow Benford's Law. If an exchange's trade value patterns violate this pattern, it's an indicator of (but not definitive proof) of manipulated behavior.[4] See Figure 1.

Volume Correlations

An assessment of how correlated an exchange's volume is relative to its peers. Well-behaved exchanges tend to behave similarly to each other, and on average have a higher correlation of relative changes in volume across time. More precisely, we expect volume to increase and decrease at the same time across exchanges in response to material releases of new information. Inversely, less-behaved exchanges are different in different ways, and thus exhibit lower correlation across the rest of the exchanges. Exchanges that manipulate their reported trading volume via artificial processes such as wash trading exhibit volume profiles that differ from their legitimate peers.[1]

Trade Permutations

An assessment of the legitimacy of the distribution of trade buy/sell flags of an exchange. Exchanges that have historically fabricated volume are known to show an even distribution of buy/sell flags when examining trade sequences, likely due to wash trading, non-economic trading activity, or other trading activity generated from an artificial process. Legitimate market activity tends to heavily skew towards several consecutive buy or sell trades due to the presence of informed traders that are willing to cross the spread and take liquidity in response to material new information.[5] See Figure 2.

Trade Sizes

A measure of how trade sizes are distributed on an exchange. Organic trading activity tends to result in a distribution which is linear when the natural log transformation is applied to both trade counts and trade sizes. This can be ascribed to the presence of retail and institutional market participants as well as the effect of liquidity constraints on order sizing. In contrast, inorganic trading activity generated from artificial processes can exhibit a different distribution with large numbers of trades executed with unusual trade sizes. The degree to which the distribution of trade sizes on an exchange follows or deviates from this distribution can be measured using the R^2 fit of a trend line with the distribution in log-log scale. See Figure 3.

Price Discovery

A measure of the lead/lag of asset prices on an exchange relative to a benchmark price. Exchanges that are centers of price discovery tend to lead price movement by an observable amount of time. This is measured using the Hayashi-Yoshida Estimator, allowing for a ranking of exchanges based on their lead/lag dynamics.[6] Exchanges found to lead other exchanges represent exchanges where price discovery occurs and thus score more favorably for this criteria.

In our implementation, we use a 24-hour sample of trades collected from each considered market and aggregate these trades onto a 10th-second time grid using volume-weighted-average price. The result is a series of prices, at 10th-second granularity, for each considered market. The Hayashi-Yoshida Estimator is calculated using these series and a reference market's time series. The time by which each market leads or lags the reference market is then identified, allowing exchanges to be ranked by their relative role in leading asset prices. See Figure 4.

Pricing Anomalies

Frequency that an anomaly in price among an exchange's most liquid asset pairs is found relative to other exchanges that offer the same asset pairs. An anomaly defined as having a price beyond 2 standard deviations across a common set of markets.

Transparency

The Transparency score is an assessment of the quality of publicly disclosed information from an exchange. This is valued using the following heuristic:

- High quality (proof of assets, liabilities, and oversight), timely (quarterly or better) Proof-of-Reserves
- Publicly disclosed financial information (quarterly or better "proofs" of assets and liabilities conducted by a third party auditor)
- Wallet disclosures, "proof" of assets but no credible proof of liabilities, ownership or oversight.

In contrast to the Regulatory Compliance category described in further detail below, the Transparency criteria here focuses on the *self-regulating* processes that an exchange offers. Criteria in this category includes the quality of an exchange's proof of reserves (where applicable), public disclosure of finances, and the public disclosure of an exchange's addresses.

Subcategories

Proof of Reserves Quality

This criteria evaluates the quality of an exchange's proof of reserves attestation. A selection of major exchanges have begun publishing proof of reserves attestations, yet a closer examination of these disclosures reveal that the attestations published are of varying quality. Quality is assessed on the basis of cryptographic verification of just assets or both assets and liabilities, the breadth of assets covered in the proof of reserves attestation, the frequency of the proof, user verification of liabilities, and the presence of a third party audit. These features are individually converted to a binary flag and then summed to create a score between 0 and 6, with 6 indicating a proof of reserves attestation with the strongest assurances. Our methodology is informed by Nic Carter's prior research on proof of reserves and updated based on .[1]

Publicly Disclosed Financials

An indicator for whether an exchange has disclosed their finances to the public. Exchanges that do not publish Proof of Reserves can get partial credit for disclosing their assets and liabilities.

Wallet Disclosures

An indicator for whether an exchange has disclosed their wallets or if they can be traced on-chain. This criteria can be thought of as a small fraction of fulfilling a complete Proof of Reserves, as this does not include proof of liabilities, a third party audit, frequent updates, or cryptographic proof of ownership.

Resilience & Security

Resilience & Security refers to how well an exchange protects its users. This criteria assesses exchanges for enacting proactive compliance measures such as complying to security standards (SOC2 Type II or ISO/IEC 27001) and penalizes exchanges for historical major market incidents (extensive pausing of withdrawals due to market conditions) and security incidents (hacks, data breaches). Incidents are weighted by recency and value lost.

Subcategories

SOC 2 Type 2 or ISO/IEC 27001

A binary flag for whether an exchange has demonstrated the ability to meet standardized security compliance procedures, such as SOC 2 or ISO/IEC 27001. Developed by the American Institute of CPAs (AICPA), SOC 2 defines criteria for managing customer data based on five “trust service principles”—security, availability, processing integrity, confidentiality and privacy. ISO/IEC 27001 is an international standard to manage information security.

Offers Insurance

A binary flag for whether an exchange offers cash or crypto insurance on customer deposits.

Security Incident History

A score for whether an exchange has suffered a major security incident, defined as a breach in the exchange that leads to the exposure of private consumer data or loss of customer funds. Major security incidents were identified by searching major news publications focused on coverage of cryptocurrencies. A score is calculated that is a function of the recency of the incident and the amount of lost value in U.S. dollars, where exchanges that have experienced a more severe loss of funds are penalized more but where any penalty decays gradually over time.

Market Incident History

A binary flag for “market incidents”, defined as whether an exchange has paused withdrawals for reasons beyond regular site maintenance or known exogenous events (such as the Ethereum Merge). An exchange can pause withdrawals due to a loss in banking relationships or in response to a serious security incident that compromises the security of their wallets.

Regulatory Compliance

The Regulatory Compliance score is an assessment on an exchange's ability to meet regulatory requirements via its existing licenses. This score focuses on whether an exchange is regulated in the jurisdiction where they do business and the *relative quality of its jurisdiction's regulators*, which accounts for the country of domicile/headquarters, registration with a regulatory body or bodies, and any additional voluntary compliance procedures.

Subcategories

Registered with a Tier 1 or Tier 2 Regulatory Agency

A binary flag for whether an exchange is registered with a Tier 1 or Tier 2 regulatory agency. A Tier 1 agency is a regulator who is a board member for the International Organization of Securities Commissions (IOSCO). A Tier 2 Agency as a regulator who is an Ordinary member of IOSCO. Special cases are made for the BitLicense (USA, Tier 1), Virtual Assets Regulatory Agency (VARA) (Dubai, Tier 1), and El Salvador (Tier 2). Exchanges regulated with a Tier 1 regulatory agency automatically achieve perfect scores. In the absence of being regulated by a Tier 1 regulatory agency, we check whether an exchange meets the subsequent criteria for partial credit.

KYC/AML

A binary flag for whether an exchange enforces Know-Your-Customer/Anti-Money-Laundering (KYC/AML) policies in order to use the exchange. An exchange is determined to enforce KYC/AML policies if enforcement is applied upon user account creation. If an exchange allows users limited abilities to deposit, withdraw, or engage in trading before verifying the user's identity, the binary flag is set to 0.

Offers Fiat Currencies

A binary flag for whether an exchange offers fiat currencies specifically for developed markets.

API Quality (Formerly Infrastructure)

The API Quality score is an assessment of an exchange's quality to be used as a programmable entity. The quality of technical infrastructure informs the ease-of-use of being able to execute actions programmatically, such as for reading data or executing trades, using an exchange's API. Quality is assessed based on quantitative and quantitative factors that the Coin Metrics team has identified from building data feeds from each exchange on this list.

Criteria in this category include the availability of an exchange's historical data and whether the exchange offers features that are critical for users who wish to collect market data or trade programmatically: a streaming API interface, a FIX API interface, a status page, trade buy/sell indicators, unique trade identifier, trade execution time, and sequential integer trade IDs. The selection of these features are informed by Coin Metrics' experience in developing and maintaining our market data collection system.

Subcategories

Historical Data

A binary flag for indicating whether an exchange allows users to query historical trades data. Exchanges differ in the amount of historical trades that are served via their API. Some exchanges only allow a user to query a fixed amount of trades, such as the past 1,000 trades that occurred on a market, or a fixed time window, such as the previous 24 hours of trades. The most transparent exchanges offer the full history of trades starting from the inception of the exchange. Exchanges that limit the ability to query historical data receive a 0 while exchanges that offer full history receive a 1.

FIX API

A binary flag indicating whether an exchange offers a FIX API interface.

Status Page

A binary flag indicating whether an exchange has a status page.

Buy/Sell Indicator

A binary flag indicating whether an exchange serves trades data with a buy/sell flag.

Unique Trade Identifier

A binary flag indicating whether an exchange's API provides a unique trade identifier.

Sequential Integer Trade ID

A binary flag indicating whether an exchange's API returns a trade ID that is ordered sequentially by time. Exchanges that offer a sequential integer trade ID allow for market participants to independently verify that they have the complete set of trades from an exchange by looking for any gaps in trade IDs.

Rate Limiting

An indicator for how well an exchange API's rate limits are commensurate to actual usage. Penalties are incurred if an exchange has no rate limits or if an exchange's rate limits are overly prohibitive. The proportion between the exchange API's rate limits and actual usage is based on empirical observations from extracting real-time data.

Outages

A metric for the duration of API outages that the exchange has experienced. Exchanges are penalized based on how long outages occur.

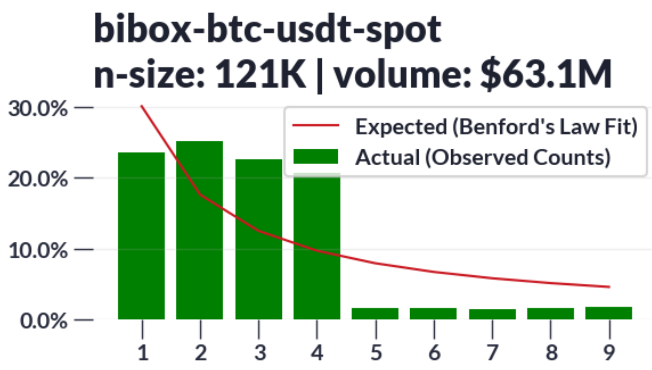
CHANGELOG

DATE	NOTES
March 1, 2023	Trusted Exchange Framework V2.0 released
October 31, 2023	Revamped Transparency, Resilience & Security, Regulatory scores; add grading scale, add rate limiting score

APPENDIX

Figure 1. Benford's Law Fits by Exchange

Organic market activity tends to follow specific properties from Benford's Law – leading digits tend to be low and most frequent, and the frequencies decrease as the leading digit increases. Markets that deviate from this behavior fail this test. The figures below illustrate the difference between a well-behaved market (binance-btc-usdt-spot) and a market that would violate this law (bibox-btc-usdt-spot). The x-axis represents the leading digits while the y-axis represents the frequency of the leading digits.



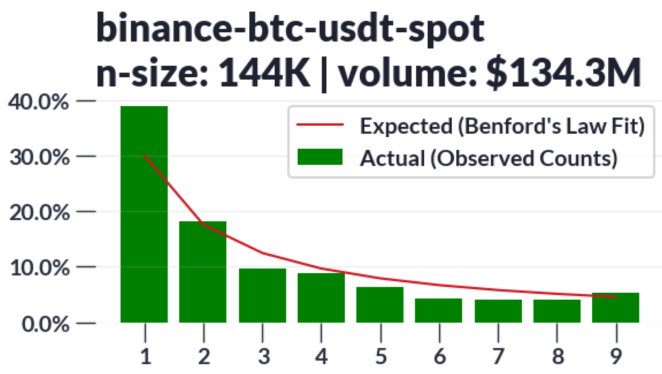


Figure 2. Trade Permutations by market-pair by exchange

The majority of well-behaved crypto markets follow trade permutation patterns with several consecutive buy or sell orders. Conversely, markets that often exhibit heavy wash trading will have a uniform distribution for their trade permutations. Below we illustrate the difference between a well-behaved market (coinbase-btc-usdt) and a market which has trade permutation patterns that are usually indicative of heavy wash trading (mexc-btc-usdc).

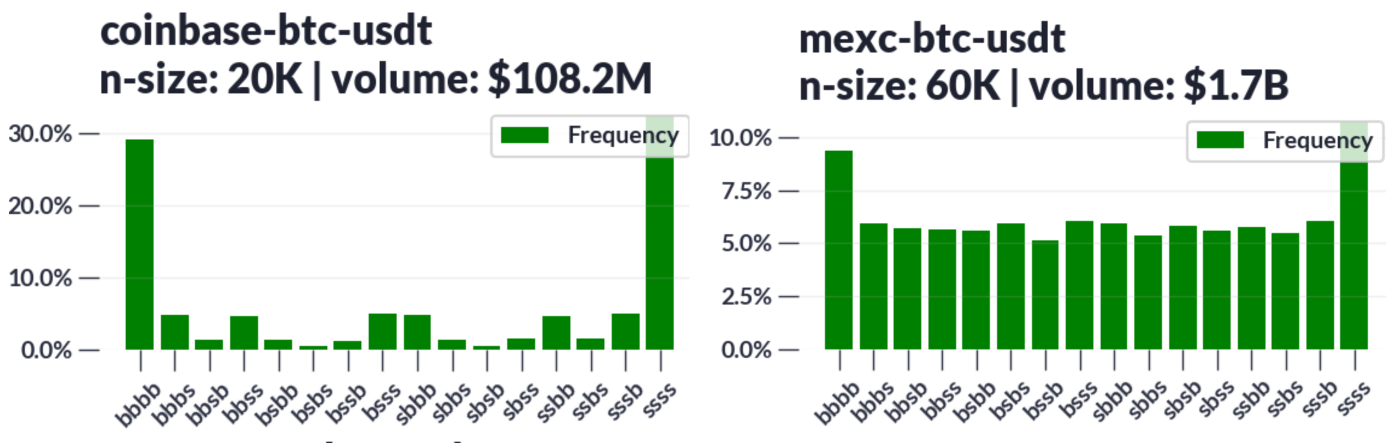
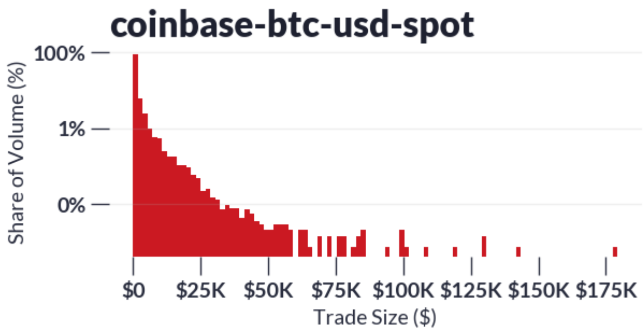


Figure 3. Trade Size Distributions

Organic trading activity tends to cause trade sizes to follow a linear distribution on doubly-logarithmic scale. Markets with significant levels of inorganic or spurious trades deviate from this distribution significantly, as can be measured by the R^2 fit of a trend line in this scale. For illustrative purposes, we plotted the raw trade size histogram between a well-behaved market (coinbase-btc-usd) and a market that does not fit this distribution (cex.io-btc-usd).



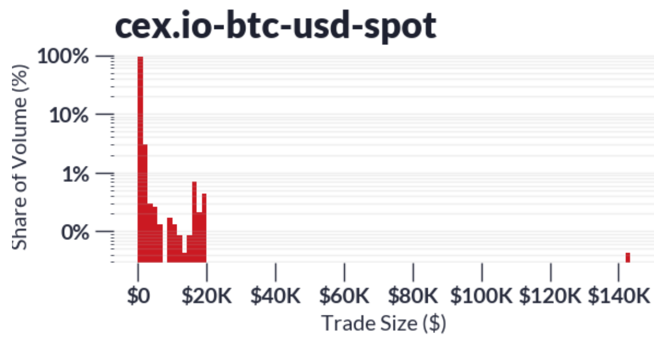


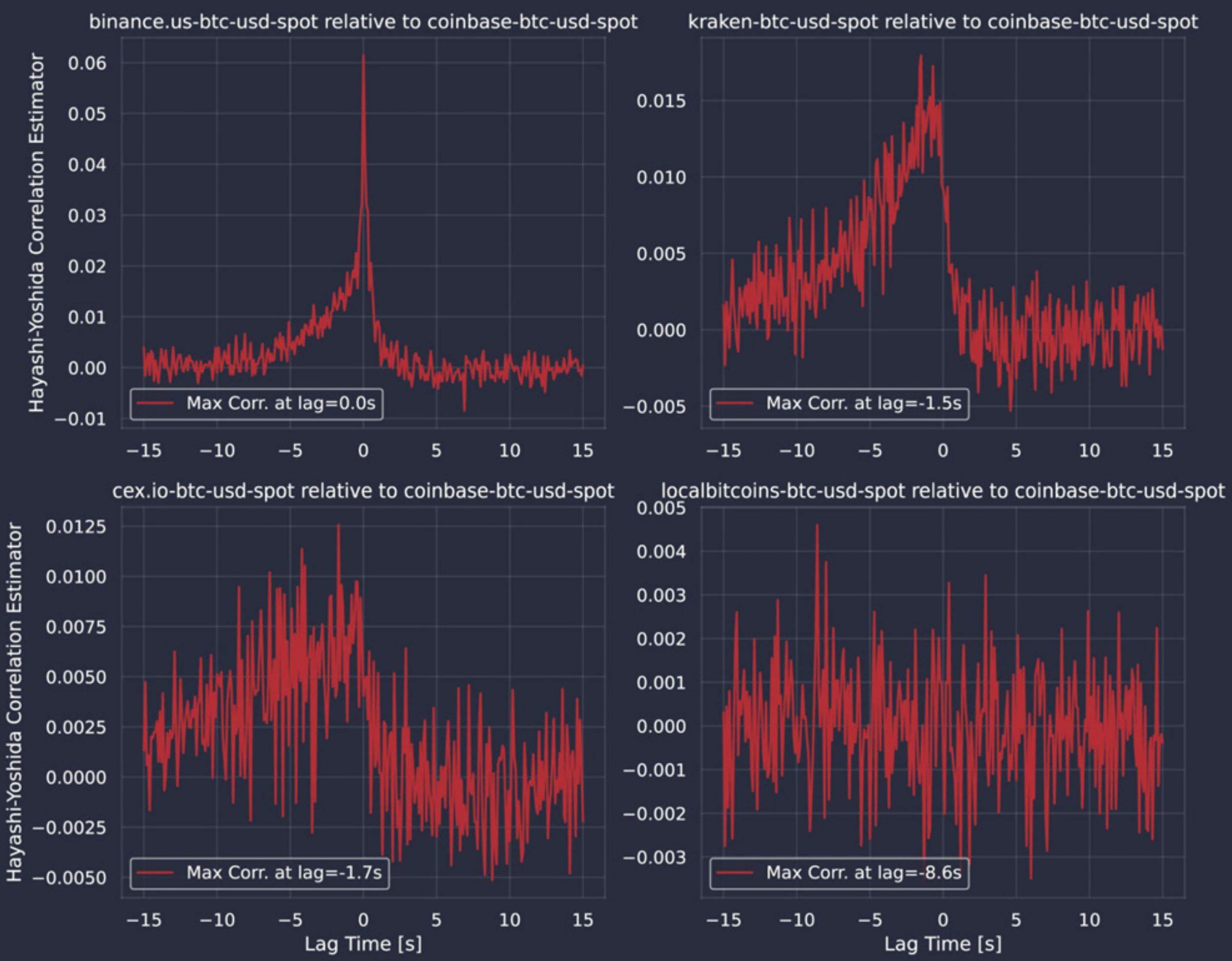
Figure 4. Price Discovery

Lag curves are a crucial component of the Hayashi-Yoshida methodology used to quantify Price Discovery. In this method, returns of an asset on one market are shifted forwards and backwards in time relative to the returns of the same asset on a reference market. Estimating the correlation between these returns, as a function of time displacement, allows for analysts to observe how much a given market should be lagged for its prices to most strongly correlate with the adjacent reference market.

Consider the lag curves for four example BTC-USD markets below, taking Coinbase as a reference exchange. Prices on Binance.us are most correlated at a lag of 0.0s, meaning that the two markets are perfectly in sync. This is not so for Kraken, where the maximum correlation occurs at -1.5s. This means that Kraken's BTC-USD market lags Coinbase by 1.5s. By measuring these lag times for multiple base assets, the aggregate lead/lag dynamics between exchanges can be quantified.

It is important to note that there are edge cases, such as LocalBitcoins in the example below. When the lag curve exhibits no strong peak, there is no meaningful lag time to be identified. In these cases, the noisy market is omitted from the calculation.

Hayashi-Yoshida Lag Curves for Example Markets



WORKS CITED

1. Carter, Nic. "The Status of Proof of Reserve as of Year End 2022." Medium, 29 December 2022, https://medium.com/@nic__carter/the-status-of-proof-of-reserve-as-of-year-end-2022-48120159377c. Accessed 30 January 2023.

2. Bitwise Asset Management. "Economic and Non-Economic Trading In Bitcoin: Exploring the Real Spot Market For The World's First Digital Commodity." SEC.gov, 24 May 2019, https://www.sec.gov/comments/sr-nysearca-2019-01/srnysearca201901-5574233-185408.pdf. Accessed 27 January 2023.

3. "More Than Half of All Bitcoin Trades Are Fake." Forbes, 10 August 2022, https://www.forbes.com/sites/javierpaz/2022/08/26/more-than-half-of-all-bitcoin-trades-are-fake/?sh=28d5007d6681. Accessed 30 January 2023.

4. Cong, Lin William, et al. "Crypto Wash Trading." https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3530220.

5. Digital Asset Research. "Clean Prices: A Required Step for Crypto to Mature." Medium, 25 October 2019, https://medium.com/digitalassetresearch/clean-prices-a-required-step-for-crypto-to-mature-bbb4156b76d8. Accessed 30 January 2023.

6. Robertson, Kevin, and Jiani Zhang. "Suitable Price Discovery Measurement of Bitcoin Spot and Futures Markets." 12 January 2022, https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4012165.

TRUSTED EXCHANGE FRAMEWORK 2.0

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